Sun *et al.*
EURASIP Journal on Advances in Signal Processing (2024) 2024:36
https://doi.org/10.1186/s13634-024-01132-4

EURASIP Journal on Advances in Signal Processing

RESEARCH **Open Access**

Performance evaluation of distributed multi-agent IoT monitoring based on intelligent reflecting surface

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Abstract

The advent of intelligent reflecting surface (IRS) technology has revolutionized the landscape of wireless communication systems, offering promising opportunities for enhancing the performance of Internet of Things (IoT) applications. This paper presents a comprehensive performance evaluation of multi-agent IoT monitoring systems leveraging IRS technology. We focus on three criteria for selecting IRS units and assess the impact on system performance. Specifically, we analyze the system performance by deriving an outage probability expression for each criterion. Our study begins by introducing the concept of IRS and its role in IoT monitoring. We then present three IRS unit selection criteria: optimal selection (OS), partial selection (PS), and random selection (RS). For each criterion, we mathematically model and analyze the system outage probability, shedding light on the reliability and connectivity of IoT devices. The outage probability expressions derived in this work offer valuable insights into the trade-offs associated with IRS unit selection criteria in the context of IoT monitoring. Additionally, our findings contribute to the optimization of multi-agent IoT monitoring systems, enabling improved communication performance and enhanced reliability.

Keywords: Multi-agent networks, Intelligent reflecting surface, Unit selection, Outage probability

1 Introduction

The development of information technology has been marked by a remarkable evolution, with wireless communication and edge computing playing pivotal roles in this transformative journey [1–3]. Wireless communication technologies have fundamentally reshaped the way we connect and communicate, enabling ubiquitous access to data and services [4–6]. From the early days of mobile phones to the advent of high-speed 5 G networks, wireless communication has grown to support a vast array of devices and applications, facilitating real-time data transfer and enabling the Internet of Things (IoT) [7–9]. Concurrently, the rise of edge computing has revolutionized data processing, bringing computational power closer to the data source [10–13]. This shift has not only reduced latency but also unlocked new possibilities for real-time decision-making and analytics at the edge, enabling applications like autonomous vehicles, smart cities, and industrial automation. The synergy between wireless communication and edge computing has laid the foundation for a future where information technology is seamlessly integrated into our daily lives, driving innovation, efficiency, and connectivity across various sectors. As these technologies continue to advance, the landscape of information technology will undoubtedly see further transformation, delivering enhanced experiences and unprecedented capabilities to users worldwide.

The development of IoT networks has seen a remarkable evolution, ushering in a new era of connectivity and data-driven insights [14–17]. Monitoring IoT networks has become a critical aspect of this development, as the sheer scale and complexity of IoT deployments demand continuous oversight [18–21]. To effectively monitor these networks, advanced technologies such as edge computing and machine learning (ML) are employed to process and analyze the vast amount of data generated by IoT devices in real time [3, 6, 22, 23]. This proactive monitoring approach enables predictive maintenance, early detection of anomalies, and efficient resource management, ensuring the optimal functioning of IoT devices and, consequently, the success of various IoT applications across industries ranging from healthcare and smart cities to agriculture and industrial automation [24–27]. As IoT networks continue to expand and diversify, monitoring solutions will play an indispensable role in maintaining their reliability, security, and performance.

Intelligent reflecting surface (IRS) is a transformative technology in wireless communication systems, significantly enhancing data rate, minimizing outage probability, and improving symbol error rate (SER). By deploying passive reflecting elements, IRS optimizes signal propagation, enabling multi-path signal control and beamforming. This results in substantial data rate enhancement as signals can be efficiently focused on the intended receivers, mitigating interference and boosting spectral efficiency. The outage probability is drastically reduced as IRS units actively respond to environmental conditions, such as path loss and fading, to ensure consistent signal coverage. Additionally, IRS enhances the SER by mitigating the effects of channel impairments, facilitating reliable and low-error communication. These combined advantages position IRS as a promising solution for the next-generation wireless networks, offering the potential to revolutionize data transmission and reliability across various applications and scenarios.

Motivated by the above literature review, this study provides a comprehensive assessment of multi-agent IoT monitoring systems empowered by IRS technology. We delve into the impact of three criteria for selecting IRS units on the system performance. In particular, our analysis centers on the derivation of outage probability expressions for each of these selection criteria. The exploration commences with an introduction to IRS and its pivotal role in IoT monitoring. Subsequently, we present three IRS unit selection criteria: optimal selection (OS), partial selection (PS), and random selection (RS). Each of these criteria is subjected to rigorous mathematical modeling and analysis to gauge their influence on the system reliability and IoT device connectivity. The outage probability expressions derived from our investigation provide valuable insights into the nuanced trade-offs inherent to different IRS unit selection criteria within the context of IoT monitoring. Moreover, our findings make meaningful contributions to the enhancement of multi-agent IoT monitoring systems, ultimately leading to improved communication performance and heightened reliability, thus advancing the realization of a seamlessly efficient IoT ecosystem.

2 System model

As shown in Fig. 1, we consider a communication based IoT monitoring system with one sender S, one destination D and one IRS composed of N units. Precisely, the absence of the direct wireless link between the source S and destination D necessitates their communication to be established indirectly through the intermediary IRS. In this network, the signal-to-noise ratios (SNRs) at S and D are given by

$$\gamma_S = \frac{P}{\sigma^2}, \tag{1}$$

$$\gamma_{Dn} = \frac{P}{\sigma^2}|g_{1n}|^2|g_{2n}|^2, \tag{2}$$

where P is the transmit power at the S, and σ^2 is the variance of the additive white Gaussian noise (AWGN). Moreover, let $|g_{1n}|^2$ and $|g_{2n}|^2$ denote the channel gains from the S to the IRS and the IRS to the D, respectively, where n denotes the n-th ($n \in \{1, 2, \ldots, N\}$) unit of the IRS, and $g_{1n} \sim \mathcal{CN}(0, \beta_1)$, $g_{2n} \sim \mathcal{CN}(0, \beta_2)$, respectively. Without loss of generality, we assume that all wireless links experience free-space path loss. Hence, β_1 and β_2 are given by,

$$\beta_1 = d_1^{-2}, \tag{3}$$

$$\beta_2 = (1 - d_1)^{-2}, \tag{4}$$

where $d_1 \in (0, 1)$ is a relative distance, and a larger d_1 results in an enhanced first-hop relaying with a weaker second-hop relaying. Then, we can obtain the transmission data rate with the assistance of the IRS as

$$R_n = \frac{1}{2}\log_2(1 + \gamma_{Dn}). \tag{5}$$

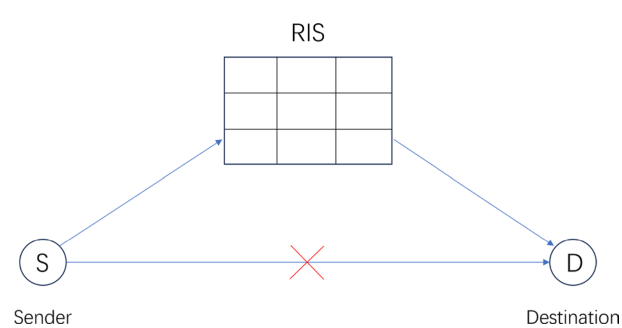

Fig. 1 IoT monitoring system assisted by IRS

3 Unit selection and performance analysis

Within this section, our initial focus lies in presenting a comprehensive analysis of the system outage probability, followed by the meticulous derivation of closed-form expressions that encapsulate the outage probability. These expressions are developed to specifically account for a range of diverse IRS unit selection criteria, ensuring a thorough understanding of the underlying dynamics and performance implications.

Firstly, the outage occurs when

$$R_n < R_{\text{th}}, \tag{6}$$

where R_{th} is the transmission rate threshold, which means the transmission rate with the assistance of the IRS R_n is lower than R_{th}. Hence, the outage probability can be denoted as

$$P_{\text{out},n} = \Pr(R_n < R_{\text{th}}), \tag{7a}$$

$$= \Pr\left(\frac{1}{2}\log_2(1+\gamma_{Dn}) < R_{\text{th}}\right), \tag{7b}$$

$$= \Pr(\gamma_{Dn} < 2^{2R_{\text{th}}} - 1 = \gamma_{\text{th}}), \tag{7c}$$

where γ_{th} denotes the SNR threshold. We can further write (7) as

$$P_{\text{out},n} = \Pr\left(\frac{P}{\sigma^2}|g_{1n}|^2|g_{2n}|^2 < \gamma_{\text{th}}\right), \tag{8a}$$

$$= \Pr\left(|g_{1n}|^2|g_{2n}|^2 < \frac{\sigma^2}{P}\gamma_{\text{th}}\right). \tag{8b}$$

In order to better utilize the IRS, we propose three IRS unit selection criteria, namely the optimal selection criterion, partial selection criterion, and random selection criterion. Next, we analyze the communication outage probabilities $P_{\text{out},n}$ under the three criteria.

3.1 Optimal selection (OS)

At the first, the optimal selection criterion means that

$$n^* = \arg\max_{1\le n\le N} \left|g_{1n}\right|^2\left|g_{2n}\right|^2. \tag{9}$$

Thus, we assume

$$X_n = |g_{1n}|^2|g_{2n}|^2, \tag{10}$$

and for X_1, its cumulative distribution function (CDF) is

$$F(X_1) = P(X_1 \le x_1), \tag{11a}$$

$$= P(|g_{11}|^2|g_{21}|^2 \le x_1), \tag{11b}$$

$$= 1 - 2\sqrt{\frac{x_1}{\beta_1\beta_2}}K_1\left(2\sqrt{\frac{x_1}{\beta_1\beta_2}}\right), \tag{11c}$$

where $K_1(\cdot)$ is the modified Bessel function of the second type.

Similarly, we can obtain the CDF of X_i as,

$$F(X_i) = 1 - 2\sqrt{\frac{X_i}{\beta_1\beta_2}}K_1\left(2\sqrt{\frac{X_i}{\beta_1\beta_2}}\right). \quad (i = 1, 2, \ldots, N) \tag{12}$$

For

$$Y = \max\{x_1, x_2, \ldots, x_N\}, \tag{13}$$

its cumulative distribution function is

$$F_Y(y) = P\{Y \leq y\} \tag{14a}$$

$$= \left[1 - 2\sqrt{\frac{y}{\beta_1\beta_2}}K_1\left(2\sqrt{\frac{y}{\beta_1\beta_2}}\right)\right]^N, \tag{14b}$$

we can further write (14b) as

$$F_Y(y) = C_N^0 1^N \left[-2\sqrt{\frac{y}{p_1\beta_2}}K_1\left(2\sqrt{\frac{y}{p_1\beta_2}}\right)\right]^0 + \cdots \tag{15a}$$

$$+ C_N^N 1^0 \left[-2\sqrt{\frac{y}{\beta_1\beta_2}}K_1\left(2\sqrt{\frac{y}{p_1\beta_2}}\right)\right]^N \tag{15b}$$

$$= \sum_{i=0}^{N} C_N^i \left[-2\sqrt{\frac{y}{\beta_1\beta_2}}K_1\left(2\sqrt{\frac{y}{\beta_1\beta_2}}\right)\right]^i \tag{15c}$$

$$= \sum_{i=0}^{N} C_N^i [-2d_1(1-d_1)\sqrt{y}K_1(2d_1(1-d_1)\sqrt{y}]^i. \tag{15d}$$

Because of

$$f_Y(y) = F_Y^{'}(y), \tag{16}$$

the outage probability of OS criterion can be given by

$$P_{\text{out},n} = \Pr\left(Y < \frac{\sigma^2\gamma_{\text{th}}}{P}\right), \tag{17a}$$

$$= \int_0^{\frac{\sigma^2\gamma_{\text{th}}}{P}} f(y)\mathrm{d}y, \tag{17b}$$

$$= \sum_{i=0}^{N} C_n^i (-1)^i [AK_1(A)]^i, \tag{17c}$$

with

$$A = 2d_1(1-d_1)\sigma\sqrt{\frac{\gamma_{\text{th}}}{P}}. \tag{18}$$

3.2 Partial selection (PS)

To simplify the analysis, we choose to derive the outage probability of the PS criterion based on the CSI of the second-hop of the IRS. At the first, the PS criterion means that

$$n^* = \arg\max_{1\le n\le N} |g_{2n}|^2. \tag{19}$$

In the same way before, we let

$$Y = \max\{|g_{21}|^2, |g_{22}|^2, \ldots, |g_{2n}|^2\}, \tag{20}$$

$$z = |g_{1\text{n}}|^2, \tag{21}$$

thus, we have

$$F_Y(y) = \left(1 - e^{\frac{y}{\beta_2}}\right)^N, \tag{22}$$

$$F_Z(z) = 1 - e^{-\frac{z}{\beta_1}}, \tag{23}$$

$$f(y) = \frac{N}{\beta_2}\left(1 - e^{-\frac{y}{\beta_2}}\right)^{N-1} e^{-\frac{y}{\beta_2}}, \tag{24}$$

$$f(z) = \frac{1}{\beta_1} e^{-\frac{z}{\beta_1}}. \tag{25}$$

From the above results, we can write the outage probability as,

$$P_{\text{out},n} = \Pr\left(z < \frac{\sigma^2\gamma_{\text{th}}}{PY}\right), \tag{26a}$$

$$= \int_0^{\infty} \int_0^{\frac{\sigma^2\gamma_{\text{th}}}{Py}} \frac{N}{\beta_2}\left(1 - e^{-\frac{y}{\beta_2}}\right)^{N-1} e^{-\frac{y}{\beta_2}} \frac{1}{\beta_1} e^{-\frac{z}{\beta_1}} \,\mathrm{d}z\mathrm{d}y, \tag{26b}$$

$$= 1 - \frac{N}{\beta_2} \sum_{i=0}^{N-1} (-1)^i C_{N-1}^i \frac{2\sigma d_1}{1-d_1} \sqrt{\frac{\gamma_{\text{th}}}{P(i+1)}} \times K_1\left(2\sigma d_1(1-d_1)\sqrt{\frac{(i+1)\gamma_{\text{th}}}{P}}\right). \tag{26c}$$

Due to

$$kC_N^k = NC_{N-1}^{k-1}, \tag{27}$$

we have

$$NC_{N-1}^i = (i+1)C_N^{i+1}. \tag{28}$$

Thus, we can rewrite (26c) as

$$P_{\text{out},n} = 1 + \sum_{i=1}^{N} (-1)^i C_N^i BK_1(B), \tag{29a}$$

with

$$B = 2\sigma d_1(1-d_1)\sqrt{\frac{i\gamma_{\text{th}}}{P}}. \tag{30}$$

3.3 Random selection (RS)

According to $|g_{1n}|^2 \sim \text{Exp}(\beta_1)$ and $|g_{2n}|^2 \sim \text{Exp}(\beta_2)$, we can obtain the probability density functions $f_{|g_{1n}|^2}(x)$ and $f_{|g_{2n}|^2}(x)$ as,

$$\begin{aligned} f_{|g_{1n}|^2}(x) &= \begin{cases} \frac{1}{\beta_1} e^{-\frac{x}{\beta_1}}, & \text{If } x > 0. \\ 0, & \text{Otherwise.} \end{cases} \\ f_{|g_{2n}|^2}(x) &= \begin{cases} \frac{1}{\beta_2} e^{-\frac{x}{\beta_2}}, & \text{IF } x > 0. \\ 0, & \text{Otherwise.} \end{cases} \end{aligned} \tag{31}$$

Then, the associated cumulative distribution functions are

$$F_{|g_{1n}|^2}(x) = 1 - e^{-\frac{x}{\beta_1}}, \tag{32}$$

$$F_{|g_{2n}|^2}(x) = 1 - e^{-\frac{x}{\beta_2}}. \tag{33}$$

Thus, we can write the outage probability as

$$P_{\text{out},n} = \Pr\left(\frac{P}{\sigma^2}|g_{1n}|^2|g_{2n}|^2 < \gamma_{\text{th}} Pr\right), \tag{34a}$$

$$= \Pr Pr\left(|g_{1n}|^2 < \frac{\sigma^2\gamma_{\text{th}}}{P|g_{2n}|^2} Pr\right), \tag{34b}$$

$$= \Pr\left(X < \frac{\sigma^2\gamma_{\text{th}}}{PY}\right), \tag{34c}$$

with

$$\left|g_{1n}\right|^2 = X, \quad \left|g_{2n}\right|^2 = Y. \tag{35}$$

Then, we can further write (34c) as

$$P_{\text{out},n} = \int_0^\infty \int_0^{\frac{\sigma^2\gamma_{\text{th}}}{PY}} f(x,y)\mathrm{d}x\mathrm{d}y, \tag{36a}$$

$$= \int_0^\infty \int_0^{\frac{\sigma^2\gamma_{\text{th}}}{PY}} \frac{1}{\beta_1}e^{-\frac{x}{\beta_1}}\frac{1}{\beta_2}e^{-\frac{y}{\beta_2}}\mathrm{d}x\mathrm{d}y. \tag{36b}$$

As

$$\int_0^{\frac{\sigma^2\gamma_{\text{th}}}{\rho y}} \frac{1}{\beta_1\beta_2}e^{-\frac{x}{\beta_1}}e^{-\frac{y}{\beta_2}}\mathrm{d}x \tag{37a}$$

$$= \frac{1}{\beta_2}e^{-\frac{x}{\beta_1}}e^{-\frac{y}{\beta_2}}\Big|^{0}_{\frac{\sigma^2\gamma_{\text{th}}}{Py}}, \tag{37b}$$

$$= \frac{1}{\beta_2}e^{-\frac{y}{\beta_2}} - \frac{1}{\beta_2}e^{-\frac{y}{\beta_2}}e^{-\frac{\sigma^2\gamma_{\text{th}}}{Py\beta_1}}, \tag{37c}$$

Equation (36) can be rewritten as

$$P_{\text{out},n} = \int_0^\infty \left(\frac{1}{\beta_2}e^{-\frac{y}{\beta_2}} - \frac{1}{\beta_2}e^{-\frac{y}{\beta_2}}e^{-\frac{\sigma^2\gamma_{\text{th}}}{Py\beta_1}}\right)\mathrm{d}y \tag{38a}$$

$$= e^{-\frac{y}{\beta_2}}\Big|^{0}_{\infty} - \int_0^\infty \frac{1}{\beta_2}e^{-\frac{y}{\beta_2}}e^{-\frac{\sigma^2\gamma_{\text{th}}}{Py\beta_1}}\mathrm{d}y \tag{38b}$$

$$= 1 - \int_0^\infty \frac{1}{\beta_2}e^{-\frac{y}{\beta_2}}e^{-\frac{\sigma^2\gamma_{\text{th}}}{Py\beta_1}}\mathrm{d}y. \tag{38c}$$

Finally, the outage probability of the RS criterion can be written as

$$P_{\text{out},n} = 1 - \frac{1}{\beta_2}\frac{2\sigma d_1}{(1-d_1)}\sqrt{\frac{\gamma_{\text{th}}}{P}}K_1(A) \tag{39a}$$

$$= 1 - AK_1(A), \tag{39b}$$

with

$$A = 2d_1(1-d_1)\sigma\sqrt{\frac{\gamma_{\text{th}}}{P}}. \tag{39c}$$

Overall, the above three selection criteria for IRS units, namely optimal selection, partial selection, and random selection, present a trade-off between the implementation complexity and outage performance. Specifically, optimal selection, while offering the best outage performance, demands a higher implementation complexity due to its requirement for extensive channel state information and computational optimization. Partial selection strikes a balance between complexity and performance by making informed choices based on partial channel knowledge. In contrast, random selection, the simplest to implement, typically results in higher outage probabilities, as it selects IRS units without considering specific performance metrics or channel conditions. The choice of selection criterion should be made by considering the specific application requirements and available resources.

4 Simulation results and discussions

In this section, we present a series of simulations aimed to verify the proposed studies. If not specified, the simulation environment is set as follows. The communication rate threshold is set to $R_{\text{th}} = 0.1$ bps/Hz, the parameter for the relative distance is $d_1 = 0.3$, and the total number of IRS units is $N = 4$. Moreover, the variance of AWGN is set to $\sigma^2 = 1$, the transmit SNR is set to $\gamma_S = 0$ dB, and the transmit power P is 1 W.

Figure 2 and Table 1 illustrate the effect of the total number of IRS units N on the analytical and simulated outage probabilities for the three unit selection criteria, where N takes values from the set $\{1, 4, 9, 16, 25, 36\}$, and R_{th} is set to 2 bps/Hz. In Fig. 2 and Table 1, we can observe that the outage probability of the OS criterion significantly decreases with an increase of N. This reduction is due to a larger number of IRS units,

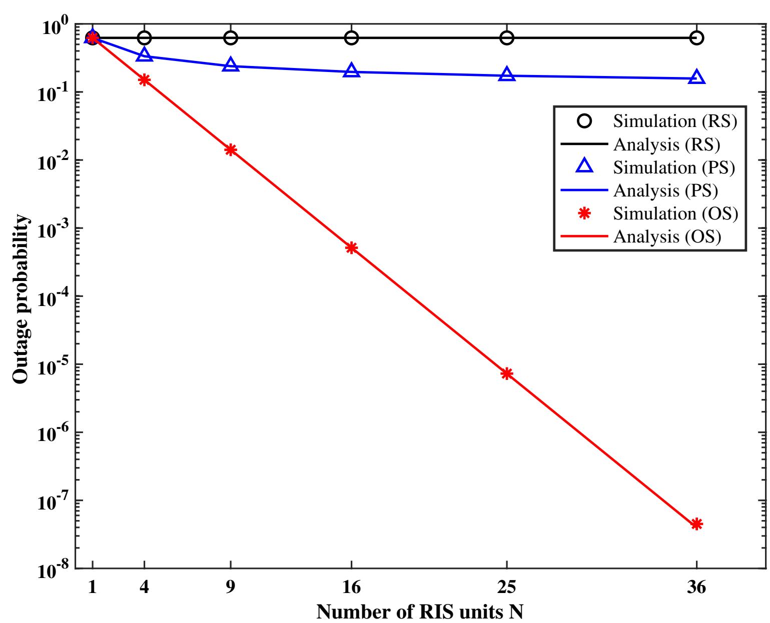

Fig. 2 Outage probability versus the number of IRS units

Table 1 Numerical outage probability versus the number of IRS units

N	1	4	9	16	25	36
Sim:RS	6.23e−1	6.23e−1	6.23e−1	6.23e−1	6.23e−1	6.23e−1
Ana:RS	6.23e−1	6.23e−1	6.23e−1	6.23e−1	6.23e−1	6.23e−1
Sim:PS	6.23e−1	3.35e−1	2.39e−1	1.97e−1	1.73e−1	1.57e−1
Ana:PS	6.23e−1	3.35e−1	2.39e−1	1.97e−1	1.73e−1	1.57e−1
Sim:OS	6.23e−1	1.51e−1	1.41e−2	5.14e−4	7.28e−6	4.50e−8
Ana:OS	6.23e−1	1.51e−1	1.41e−2	5.14e−4	7.26e−6	3.98e−8

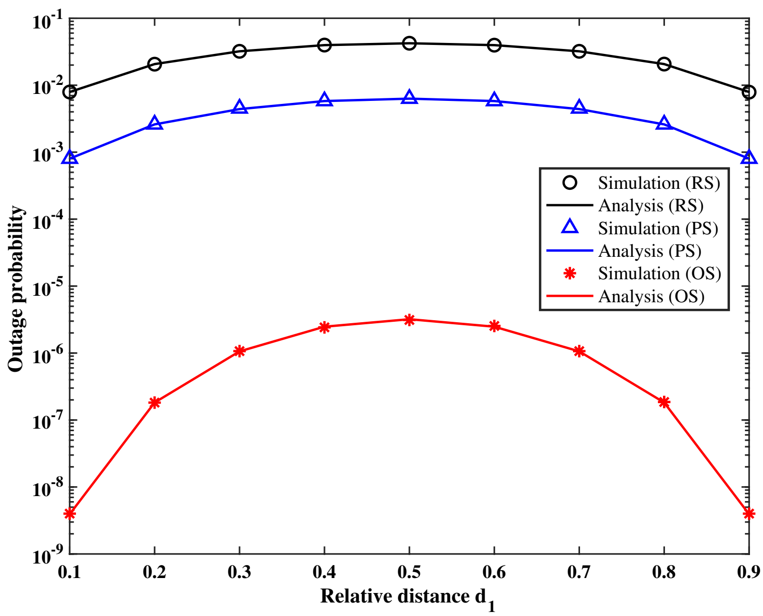

Fig. 3 Outage probability versus the relative distance d_1

which increases the capacity of the IRS. Additionally, the OS criterion consistently outperforms the other two criteria. Specifically, at $N = 25$, the simulated outage probability of the OS criterion is approximately 7.28×10^{-6}, the simulated outage probability of the PS criterion is about 1.73×10^{-1}, and the simulated outage probability of the RS criterion is approximately 6.23×10^{-1}. Moreover, the analytical and simulation solutions perfectly overlap, providing evidence for the validity of the derived expressions on the system outage probability.

Figure 3 shows the impact of the relative distance d_1 on the analytical and simulated outage probabilities of the three unit selection criteria, where d_1 varies from 0.1 to 0.9. As shown in Fig. 3, we can see that the outage probability shows an increasing and then decreasing trend with d_1, which indicates that the system has a high outage probability when the IRS is in the middle of S and D. Moreover, the analytical results overlap with the simulation results, verifying the closed-form solutions. In further, the outage probability under the OS criterion is consistently lower than that under the RS and PS criteria. Specifically, at $d_1 = 0.9$, the simulated outage probability of the OS criterion is approximately 4.00×10^{-9}, the simulated outage probability of the

PS criterion is about 8.00×10^{-4}, and the simulated outage probability of the RS criterion is approximately 7.87×10^{-3}. This is because that the OS criterion effectively utilizes the IRS to assist the communication.

Figure 4 shows the simulated and analytical results versus the data rate threshold R_{th}, where the threshold R_{th} increases from 0.1 to 1 bps/Hz. From Fig. 4, it can be seen that the outage probabilities in the communication links increase as R_{th} increases, which indicates that a smaller R_{th} leads to an improved outage performance. Moreover, the analyzed results overlap with the images of the simulation results, verifying the closed-form solution. In further, the outage probability of the OS criterion is higher than that of the PS and RS criteria. Specifically, at $R_{\text{th}} = 1$ bps/Hz, the simulated outage probability of the OS criterion is approximately 5.93×10^{-3}, the simulated outage probability of the PS criterion is about 8.40×10^{-2}, and the simulated outage probability of the RS criterion is approximately 2.77×10^{-1}.

Figure 5 depicts the comparison of the simulated and analytical system outage probabilities versus the transmit SNR γ_S, which varies from −5 to 5 dB. From Fig. 5, the congruence between the analytical and simulated results validates the accuracy of the derived expression for outage probability. Moreover, a higher γ_S yields an improved overall outage performance due to increased γ_S at the S, resulting in higher receive SNR at the D. Notably, the OS criterion consistently outperforms the other criteria, which is because that it can effectively leverage the increasing γ_S through IRS to significantly enhance outage performance. Specifically, at SNR = 5 dB, the simulated outage probability of the OS criterion is approximately 2.20×10^{-8}, the simulated outage probability of the PS criterion is about 1.40×10^{-3}, and the simulated outage probability of the RS criterion is approximately 1.25×10^{-2}.

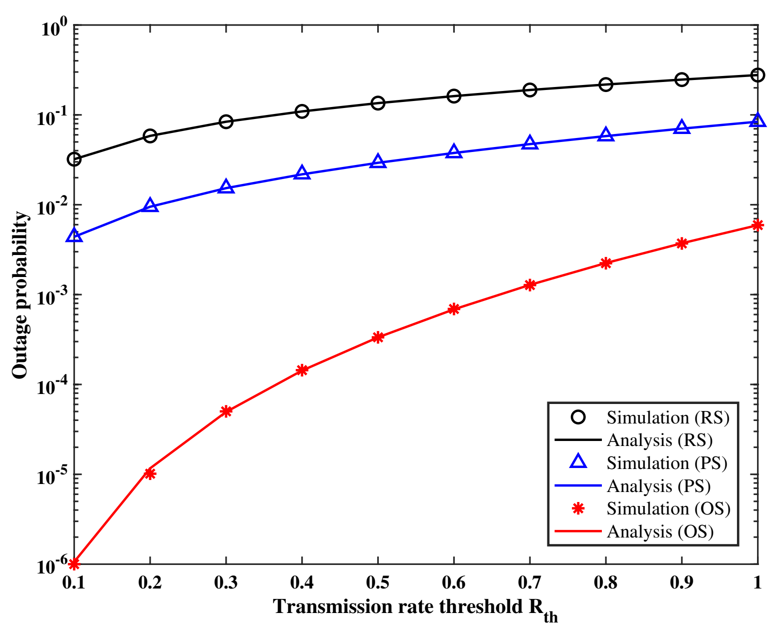

Fig. 4 Outage probability versus the data rate threshold R_{th}

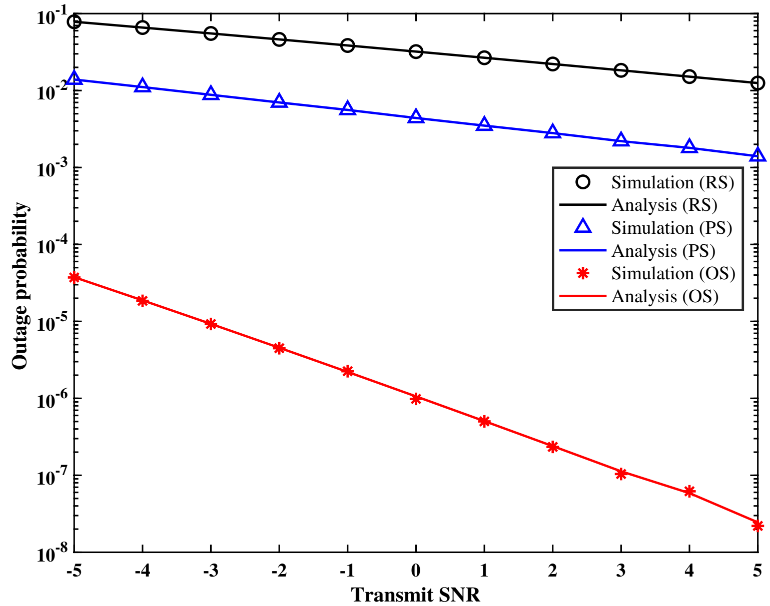

Fig. 5 Outage probability versus the transmit SNR

5 Conclusion

This paper investigated the usage of IRS in the efficiency of IoT monitoring systems within wireless communication environments. Three IRS unit selection criteria, namely optimal selection, partial selection, and random selection, were considered for enhancing the system performance. The derived outage probability expressions provided valuable insights into the trade-offs inherent in each selection criterion, allowing for informed decision-making in IoT monitoring deployments. By optimizing IRS-based IoT systems, we were able to substantially enhance communication performance and bolster reliability, thereby contributing to the ongoing development of a seamless and efficient IoT ecosystem. This study underscored the potential of IRS technology to reshape the landscape of IoT applications and laid the groundwork for further research and practical implementations in this evolving field.

Abbreviations

IRS	Intelligent reflecting surface
IoT	Internet of Things
OS	Optimal selection
PS	Partial selection
RS	Random selection
ML	Machine learning
SER	Symbol error rate
SNR	Signal-to-noise ratio
AWGN	Additive white Gaussian noise (AWGN)
CDF	Cumulative distribution function

Acknowledgements

This work was supported in part by the 2022 information special research project of China Southern Power Grid Corporation "Research on the theory of Digital Power Grid."

Author contributions

YS was responsible for designing the proposed approach, JH was responsible for performing the simulations, and FW was responsible for the writing in the manuscript.

Funding
This work was supported in part by the 2022 information special research project of China Southern Power Grid Corporation "Research on the theory of Digital Power Grid."

Availability of data and materials
The data for this study can be acquired by emailing the authors.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
All authors of this paper agree to publish the work in this paper.

Competing interests
The authors declare that they have no competing interests.

Received: 13 October 2023 Accepted: 3 March 2024
Published online: 14 March 2024

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